



# Hydrological application of radar rainfall nowcasting in the Netherlands

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## ABSTRACT

Accurate and robust short-term rainfall forecasts (nowcasts) are useful in operational flood forecasting. However, the high temporal and spatial variability of rainfall fields make rainfall nowcasting a challenging endeavour. To cope with this variability, nowcasting techniques based on weather radar imagery have been proposed. Here, we employ radar rainfall nowcasting for discharge predictions in three lowland catchments in the Netherlands, with surface areas ranging from 6.5 to 957 km<sup>2</sup>. Deterministic (Lagrangian persistence) and probabilistic (SBMcast) nowcasting techniques are used to produce short-term rainfall forecasts (up to a few hours ahead), which are used as input for the hydrological model WALRUS. Rainfall forecasts were found to deteriorate with increasing lead time, often due to underestimation. Discharge could be forecasted 25–170 min earlier than without rainfall nowcasting, with the best performance for the largest catchment. When accounting for catchment response time, the best (but most variable) relative performance was found for the smallest catchment. Probabilistic nowcasting effectively accounted for the uncertainty associated with rainfall and discharge forecasts. The uncertainty in rainfall forecasts was found to be largest for the smaller catchments. The uncertainty in how much earlier the discharge could be forecasted (the gain in lead time) ranged from 15 to 50 min.

## 1. Introduction

Extreme rainfall events can lead to severe floods, which cause substantial damage. These extreme rainfall events are likely to become more intense and frequent when climate changes (Field, 2012; Klein Tank et al., 2014). When accurate forecasts of rainfall are available with a high spatial and temporal resolution, more time is available to take real-time measures that reduce damage. However, it is difficult to forecast rainfall accurately, because rainfall fields are highly variable in space and time (Berenguer et al., 2005).

During the last decades, different methods have been developed for short to medium term rainfall forecasting (0–60 h ahead). One of the available tools for such forecasts is Numerical Weather Prediction (NWP). Unfortunately, the effective resolution of NWP is relatively coarse and forecasting convective showers remains difficult, limiting their usefulness for smaller catchments with fast response times (Golding, 2009; Liguori et al., 2012; Alfieri et al., 2012).

For very short term forecasts (nowcasts) of rainfall at finer spatial and temporal scales, radar nowcasting is a possible solution. Among the different existing radar-based nowcasting methods (see e.g. Wilson et al., 1998; Pierce et al., 2012), field-advection methods permit coupling of the rainfall nowcasts with a rainfall-runoff model (e.g.

Berenguer et al., 2005). Nowcasting techniques can be divided into deterministic and probabilistic methods. Deterministic methods will lead to only one nowcast for every time step, while probabilistic nowcasts often generate ensembles, i.e. multiple nowcasting scenarios for every time step, with the aim of quantifying the predictability. Examples of probabilistic methods that are not based on ensembles are those described by Germann and Zawadzki (2004) and Kober et al. (2013). Ayzel et al. (2019) provide a recent overview of the state of the art of radar rainfall nowcasting.

Deterministic methods for radar rainfall nowcasting are for instance TREC, COTREC, MAPLE or S-PROG (Rinehart and Garvey, 1978; Li et al., 1995; Germann and Zawadzki, 2002; Seed, 2003). These methods use past radar images to derive the motion field of precipitation. This motion field is then kept stationary and used to extrapolate the rainfall field in time (Lagrangian persistence). The methods differ slightly in the way small-scale features are being treated. Such deterministic methods only give reasonable estimates of rainfall at short time scales, up to a few hours ahead. Despite their short forecasting window, deterministic nowcasting methods can still be useful for hydrology and be employed to reduce damage or casualties, especially for forecasting extreme discharges in rapidly responding catchments.

Several studies have used deterministic rainfall nowcasting for

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discharge forecasting, such as Berenguer et al. (2005) and Vivoni et al. (2006). They showed that extending the rainfall input with nowcasted rainfall, and using that as a forcing for a hydrological model, led to an increase of forecasting skill of flash floods. The extent of this increase differed between catchments, with a stronger increase for larger catchments, which is probably related to a reduced uncertainty in rainfall prediction (more pixels). Berenguer et al. (2005) studied the hydrological validation of the nowcasting techniques S-PROG and Lagrangian persistence. S-PROG (which stands for Spectral Prognosis) is an advection-based nowcasting system based on the common observation that large features in a rain field evolve more slowly than small features (Seed, 2003). They showed that S-PROG produced slightly better rainfall nowcasts, but there was no significant improvement of the discharge forecasts compared to Lagrangian persistence. They also showed that the gain in lead time with rainfall nowcasting is highly dependent on the type of catchment and the type of rainfall event. In general they found that using radar-based nowcasting significantly extends the lead time for which discharge can be forecasted accurately.

Over the last decade, methods have been developed for ensemble rainfall nowcasting based on extrapolation of radar data, which are especially suited for short term (0–3 h) rainfall forecasts at spatial resolutions as fine as  $\sim 1 \text{ km}^2$  (Bowler et al., 2006; Berenguer et al., 2011). The main goal of ensemble nowcasting is to address the uncertainty in the rainfall nowcast and subsequently the discharge forecast. Examples of methods for creating short-term ensemble rainfall nowcasts are the Short-Term Ensemble Prediction System (STEPS; Bowler et al., 2006) and SBMcast (Berenguer et al., 2011). Both methods are designed such that they produce an ensemble of equally likely rainfall nowcasts, by perturbing the rainfall patterns for every ensemble member with a second-order autoregressive process.

STEPS and SBMcast have been used as radar nowcasting methods by Berenguer et al. (2011), Liguori and Rico-Ramirez (2012), Seed et al. (2013) and Foresti et al. (2016). Foresti et al. (2016) showed that for two Belgian cities, STEPS had a high skill in nowcasting events with a minimum rainfall amount of 0.5 mm up to a lead time of 60–90 min. For convective events exceeding 5.0 mm, this skill was only found up to a lead time of 30 min. This study also led to an operational method to use STEPS in real-time nowcasting, STEPS-BE in which a 20-member ensemble rainfall nowcast is being produced in real time, at a spatial resolution of  $0.9 \text{ km}^2$  and a temporal resolution of 5 min, up to a lead time of 2 h. This ensemble of 20 nowcasts gives insight in the uncertainty of the forecasted rainfall. Berenguer et al. (2011) developed SBMcast for creating short-term ensemble forecasts. The results show that SBMcast is able to reasonably reproduce the evolution of the rainfall field and that the ensemble gives insight in the uncertainty of the rainfall forecast. Seed et al. (2013) and Liguori and Rico-Ramirez (2012) showed that blending the rainfall nowcasts of STEPS with NWP produces promising results for short-term rainfall forecasting.

Ensemble rainfall nowcasts have found their first applications in hydrological forecasting around the world in recent years (Liu et al., 2012; Foresti et al., 2016; Liechti et al., 2013; Codo and Rico-Ramirez, 2018; Poletti et al., 2019). For STEPS, a few rather limited studies have been performed on its hydrological application (Liguori et al., 2012; Xuan et al., 2014). Liguori et al. (2012) used STEPS in combination with NWP to make deterministic and ensemble rainfall nowcasts. These rainfall nowcasts were used to simulate discharge in an urban catchment. They concluded that there was no systematic difference between the forecasted discharge based on the deterministic rainfall nowcast and the mean of the ensemble members of the probabilistic forecast, though Foresti et al. (2016) mention that ensemble averaging filters out the unpredictable precipitation features and is rewarded in terms of RMSE. Xuan et al. (2014) used STEPS in combination with a rainfall-runoff model for a small catchment in the UK. Their analysis showed that, for a small catchment, STEPS can forecast rainfall accurately and thereby improve discharge forecasts. The ensemble nowcasting also gave insight into the uncertainty of the rainfall and discharge forecasts.

To the best of our knowledge, no studies have been performed with any sort of rainfall nowcasting, either deterministic or probabilistic, for Dutch catchments thus far. Nowcasting methods could be beneficial for Dutch water boards, because there are numerous small catchments and polder areas with fast response times, where radar rainfall nowcasting can be expected to yield promising results. After implementing radar nowcasting, real-time decisions could be made to reduce damage, which would fit in the current Dutch policy of “smart water management”. At present, several Dutch water boards use decision support systems (e.g. Delft-FEWS; Werner et al., 2013), which are used operationally in discharge forecasting. NWP forecasts currently provide the main rainfall inputs to these systems. We claim that these can be complemented with high-resolution radar-based nowcasts.

In this context, the main objective of this study is to determine the added value of radar-based rainfall nowcasting for discharge forecasting in several lowland catchments in the Netherlands. We investigate (1) the skill of deterministic nowcasting for different types of rainfall events, (2) the skill of deterministic and ensemble nowcasting in forecasting peak discharges for intense rainfall events (3) the variation of this skill between events and catchments. As in Berenguer et al. (2005), the skill of the discharge forecasts is determined by comparing simulated hydrographs based on forecasted rainfall with simulated hydrographs based on observed rainfall. By avoiding a comparison of forecasted with observed discharges, the skill of the nowcasting methods is determined objectively, i.e. independent of the quality of the hydrological simulation model. Section 2 describes the field sites and data and Section 3 deals with the methods used in this study. The results for both deterministic and ensemble nowcasting are provided in Section 4. A general discussion is given in Section 5. The deterministic and ensemble nowcasting are brought together in Section 6, the conclusion of this work.

## 2. Field sites and data

### 2.1. Catchments

Three catchments were used for the hydrological validation of the nowcasting methods: the Regge ( $957 \text{ km}^2$ ), Grote Waterleiding ( $40 \text{ km}^2$ ) and Hupsel Brook ( $6.5 \text{ km}^2$ ) catchments. These were chosen for their size difference and location. They all lie in eastern part of the Netherlands (Fig. 1), ensuring enough lead time to detect rainfall systems approaching the catchments with the two weather radars operated by the Royal Netherlands Meteorological Institute (KNMI) given the prevailing wind direction (westerly). Their proximity increases the probability that a certain rainfall event affects all three catchments.

All catchments are predominantly covered by grassland, with some crops (mostly maize), forest and urbanized areas. Soils mainly consist of sand and loamy sand. Elevation differences are mild in the Hupsel Brook catchment, small in the Regge catchment and very small in the Grote Waterleiding catchment. All catchments are freely draining, but in the Grote Waterleiding about  $0.009 \text{ mm h}^{-1}$  of surface water is supplied from April to September to maintain the desired water levels. Response times are about 7–10 h for the Regge, 11–16 h for the Grote Waterleiding and 4–5 h for the Hupsel Brook. For more detailed information concerning these catchments, see Loos (2015), Heuvelink (2016) and Brauer et al. (2014).

### 2.2. Events

The annual rainfall sum in the study area is about 825 mm, which is almost equally distributed over the seasons. However, there is a difference in rainfall structure between the seasons. The winter period is dominated by stratiform rainfall events which can last up to a few days. In summer, there are stratiform events, convective events and combinations of these. To test the nowcasting method for different types of events, six rainfall events have been selected to study the skill of the



**Fig. 1.** Locations of the three study catchments (blue shaded areas) and two weather radars (red pluses) in the Netherlands (50.8–53.4°N; 3.6–7.1°E). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

nowcasting method (Table 1), of which two were also used for the ensemble nowcasting (see Section 3.2). The development and spatial patterns of the storms were visually analysed and classified as stratiform or a combination of stratiform and convective. These events were not only selected based on the rainfall amounts and structure, but also on whether they produced a significant hydrological response in the Regge catchment. Due to the dry initial conditions in summertime, no purely convective events could be used in this study, since these did not lead to pronounced hydrological responses. The Regge was used because it is the largest of the three catchments and we assumed that a rainfall event that led to a substantial increase in discharge in the Regge would also affect the two smaller catchments. Rainfall events that led to discharge peaks in the Hupsel Brook catchment may have been local and not impacted the Regge.

### 2.3. Radar product

We used the unadjusted 5-min 1-km<sup>2</sup> radar rainfall product from the Royal Netherlands Meteorological Institute (KNMI), which was constructed by combining reflectivity measurements from two radars (Fig. 1). This radar product is available in real time. For further details, see Overeem et al. (2009). To compute the catchment average precipitation, we used all pixels whose centerpoints are within the catchment boundary.

**Table 1**

Characteristics of the selected events, with rainfall sum (based on rain gauge measurements) and (measured) discharge of the Regge. In the column Type, S stands for stratiform, C for convective and C/S for a combination of both.

Event No.	Start [UTC]	End [UTC]	Duration [h]	Rainfall sum [mm]	$Q_{\max}$ [mm h <sup>-1</sup> ]	Type
1	2008-01-17 12:00	2008-01-26 11:55	216	66.1	0.197	S
2	2008-09-29 12:00	2008-10-04 23:55	108	53.9	0.120	C/S
3	2009-03-04 12:00	2009-03-07 23:55	84	21.4	0.127	S
4	2009-07-08 00:00	2009-07-12 11:55	108	45.4	0.068	C/S
5	2010-08-25 12:00	2010-08-30 23:55	132	137.9	0.351	C/S
6	2010-11-03 00:00	2010-11-08 23:55	144	41.3	0.163	S

## 3. Methods

### 3.1. Deterministic nowcasting method

In this study Lagrangian persistence was used as the deterministic forecasting method. According to this method, the rainfall field is tracked and extrapolated. Tracking was done with a modified version of COTREC (Li et al., 1995) used by Berenguer et al. (2011). For this purpose three observed radar rainfall fields were used: one at the observation time and two at 10 and 20 min before the observation time. From these rainfall fields the motion field of the rainfall system was determined. This motion field was used in the second step to advect the rainfall field. In this extrapolation step, the motion field was kept constant and processes of growth and decay of rainfall were not included. This nowcasting method was used to issue nowcasts of rainfall every five minutes up to three hours ahead, with a temporal resolution of five minutes.

### 3.2. Probabilistic nowcasting method

The goal of an ensemble forecast is to give insight in the uncertainty associated with the forecasted rainfall by the deterministic nowcasting method (the Lagrangian persistence). SBMcast is used to create this ensemble (Berenguer et al., 2011). SBMcast uses a stochastic model (the “string of beads” model or SBM) to describe the wet area ratio (indicating what part of the area is experiencing rainfall above a certain threshold) and the image mean flux (corresponding to the average rainfall rate). The ensemble members differ because the wet area ratio and image mean flux evolve differently with lead time. The stochastic model is conditioned on the observations to preserve the spatial and temporal scales of the rainfall field. The same motion field is used for the deterministic nowcasting scenario. The motion field is kept stationary, so errors in the motion field are not considered in SBMcast. A more detailed description of SBMcast can be found in Berenguer et al. (2011).

For this study, 10 ensemble members were created every five minutes, up to a lead time of two hours, with a temporal resolution of five minutes. Running a period of five days with a temporal resolution of five minutes and a spatial resolution of 1 km<sup>2</sup> took 15 days on a computer with 8 GB RAM. Therefore, it was considered too computationally expensive to make forecasts for all events and only events 5 and 6 of Table 1 were considered for this investigation.

### 3.3. Hydrological model

We used the Wageningen Lowland Runoff Simulator (WALRUS) to simulate discharges. WALRUS is a lumped rainfall-runoff model, specifically developed by Brauer et al. (2014) for lowland catchments with shallow groundwater tables. It is used by several Dutch water boards in their decision support systems, including the one for the Regge catchment.

There are three coupled reservoirs in WALRUS: a soil reservoir (with combined saturated and unsaturated zone), a quickflow reservoir and a

**Table 2**

WALRUS parameters for the three catchments. For all catchments, parameter  $a_S$  was set to 0.01 and the soil type was assumed to be loamy sand. For the Hupsel Brook catchment, instead of  $c_S$ , a stage-discharge relationship was used.

Catchment	$c_W$ [mm]	$c_V$ [h]	$c_G$ [mm h]	$c_Q$ [h]	$c_S$ [mm h <sup>-1</sup> ]	$c_D$ [mm]	Reference
Regge	396	45.0	$16 \times 10^6$	7.5	0.2	2450	Loos (2015)
Grote Waterleiding	340	10.0	$20 \times 10^6$	35.0	3.0	2200	Heuvelink (2016)
Hupsel Brook	356	0.2	$5 \times 10^6$	3.3	–	1500	Brauer et al. (2014)

surface water reservoir. To run the model, at least rainfall and potential evapotranspiration time series have to be provided. Additional forcings (e.g. surface water supply for the Grote Waterleiding catchment) can be added. The model simulates among others discharge, actual evapotranspiration and groundwater table depth. Computational efficiency and numerical stability are achieved with a flexible time step approach. Forcing data are aggregated accordingly. WALRUS has five parameters which have to be calibrated for each catchment: wetness index parameter  $c_W$ , vadose zone relaxation time  $c_V$ , groundwater reservoir constant  $c_G$ , quickflow reservoir constant  $c_Q$  and bankfull discharge  $c_S$ . In addition, some settings (parameters channel depth  $c_D$  and surface water area fraction  $a_S$  and the soil type) are based on catchment characteristics. The model was applied previously to the three catchments used in this study, so no additional calibration was needed here. Table 2 gives the used parameter values.

### 3.4. Evaluation of deterministic nowcasts

The rainfall forecasted with Lagrangian persistence was validated at the catchment scale, by averaging the rainfall of all radar pixels covering the catchments. Rainfall forecasts per catchment were compared to radar-observed 5-min rainfall sums using the relative rainfall error (the difference between forecast and observation). Because there was no forecast for all time steps for the first three hours of an event, these hours were not considered for the calculation of the relative rainfall error.

The hydrological validation of the nowcasting method consisted of the analysis of the multiple step ahead discharge forecasts, investigating the differences between the forecasted hydrographs and a reference hydrograph, following the approach of Berenguer et al. (2005). For each time step, rainfall time series have been constructed with the radar observations up to that time step and three hours of nowcasted rainfall, mimicking real-time conditions. The rainfall after these three hours was set to zero. Three examples of such rainfall time series are shown in the top row of Fig. 2.

WALRUS was run with all these rainfall input series, creating the same number of forecasted hydrographs. Initial conditions were found for each event by running WALRUS for several years (2007–2010) and taking the groundwater depth and discharge at the start of each event, from which all four state variables (storage deficit, groundwater depth, quickflow reservoir level and surface water level) could be derived (Brauer et al., 2014).

To determine the time until discharge was still forecasted reasonably well, the following procedure was used. For every lead time (the lead time for the discharge), one discharge forecast at every time step was taken. The middle row of Fig. 2 shows this for a lead time of 8 h. Combining all discharges that corresponded to a lead time of eight hours led to the constructed hydrograph in the bottom row. Note that this is not an actual hydrograph, because it is not composed of one single discharge time series, but constructed using one forecasted discharge value from all forecasted discharge series. The hydrographs constructed with different lead times were compared to a reference hydrograph, to determine their added value in terms of discharge

predictability. The reference hydrograph employed in this study was the WALRUS run with the measured radar rainfall time series as input.

The hydrographs constructed for different lead times were tested against the reference discharge in terms of the Nash-Sutcliffe (NS) efficiency, i.e. the fraction of explained variance. The threshold NS efficiency above which the discharge was still considered to be of high enough quality was set at  $NS = 0.9$ . The lead time up to which the discharge forecast was still considered acceptable, was the longest lead time for which NS exceeded 0.9. Lead times up to 15 h, with a five minute interval were used. This had to be extended to 20 h for event 1 in the Grote Waterleiding catchment, since the slow response resulted in an NS efficiency above 0.9 with a lead time of 15 h.

To determine the added value of radar rainfall nowcasting, the performance was tested against the results one would obtain without nowcasting. Therefore the same procedure as above was repeated, but now with the forecasted rainfall set to zero. Recall that a catchment's response time makes it possible to forecast discharge even without rainfall forecasts.

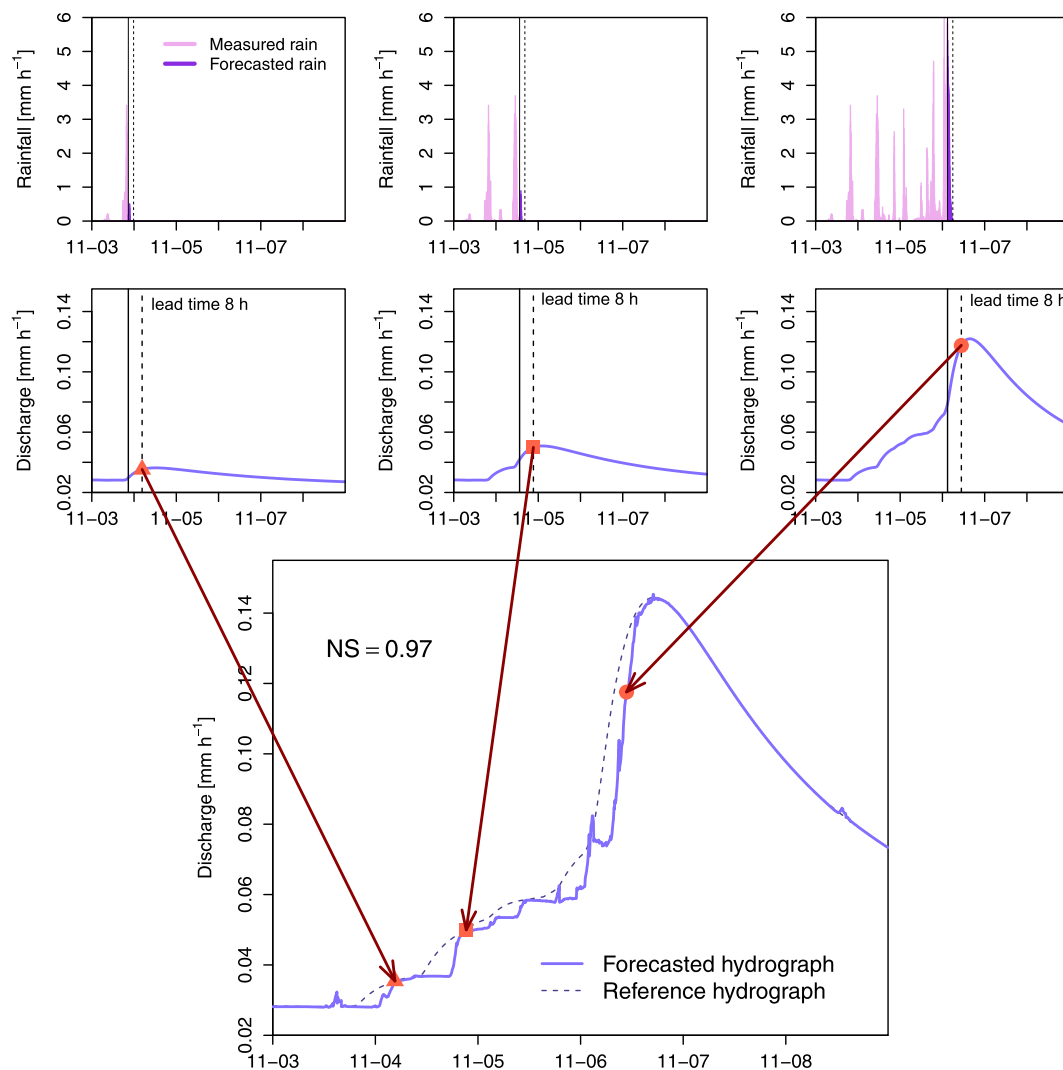
To calculate the gain in lead time caused by the rainfall nowcast, we calculated the difference in lead time yielding  $NS = 0.9$  between the discharge forecasted without nowcasting and that with a radar rainfall nowcast of 1, 2 or 3 h. This extra time gain until the discharge could still be forecasted reasonably well was solely attributable to the nowcast.

We also assessed the relative gain in lead time, because a gain of one hour is worth more for faster responding catchments than for slower responding catchments. The relative gain in lead time was derived by comparing the gain in lead time with the lead time until the discharge without forecasted rainfall could still be forecasted with a NS efficiency of 0.9.

### 3.5. Evaluation of probabilistic nowcasts

Because of the long run times of our hydrometeorological nowcasting scheme only events 5 and 6, which were also used in the deterministic nowcasting exercise, were employed to study the added value of ensemble forecasting. To reduce the computational burden, the events were not considered in their entirety. There was hardly any difference between the gain in lead time for the whole event and that for the same event, while only taking the time before the discharge peak into account. Therefore, for the ensemble forecasting exercise, only the time up to and including each discharge peak was considered.

The validation of the rainfall forecasts was performed in a similar way as for the deterministic nowcasting. The nature of the ensemble members required an extra step compared to the deterministic nowcasting case. The ensemble members all have a random component, so there is no coherence between ensemble members for different times. For instance, the forecasted rainfall for ensemble member 2 one hour in advance at 12.00 can be the highest of all members. One time step later (12.05) the forecasted rainfall for ensemble member 2 one hour in advance can be the lowest. Therefore, the 10th, 25th, 50th, 75th and 90th percentiles of 5-min rainfall sums were computed from the 10 forecasts for every time step and forecast lead time. The method with



**Fig. 2.** Graphical explanation of the construction of the forecasted hydrograph. The top row shows three example rainfall input series, with in pink the measured radar rainfall and in purple the three hours of forecasted rainfall (between the solid vertical lines indicating the current time, and the dashed vertical lines indicating three hours ahead). The middle row shows the discharge simulated by WALRUS with the rainfall input from the top row, with the solid vertical line showing the current time and the dashed vertical lines indicating eight hours ahead. As an example, the bottom row shows the construction of the forecasted hydrograph with a lead time of eight hours, compared to the reference hydrograph. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

which those percentiles were derived is that described by Hyndman and Fan (1996). For these percentiles, the relative rainfall error was calculated in the same way as in Section 3.4.

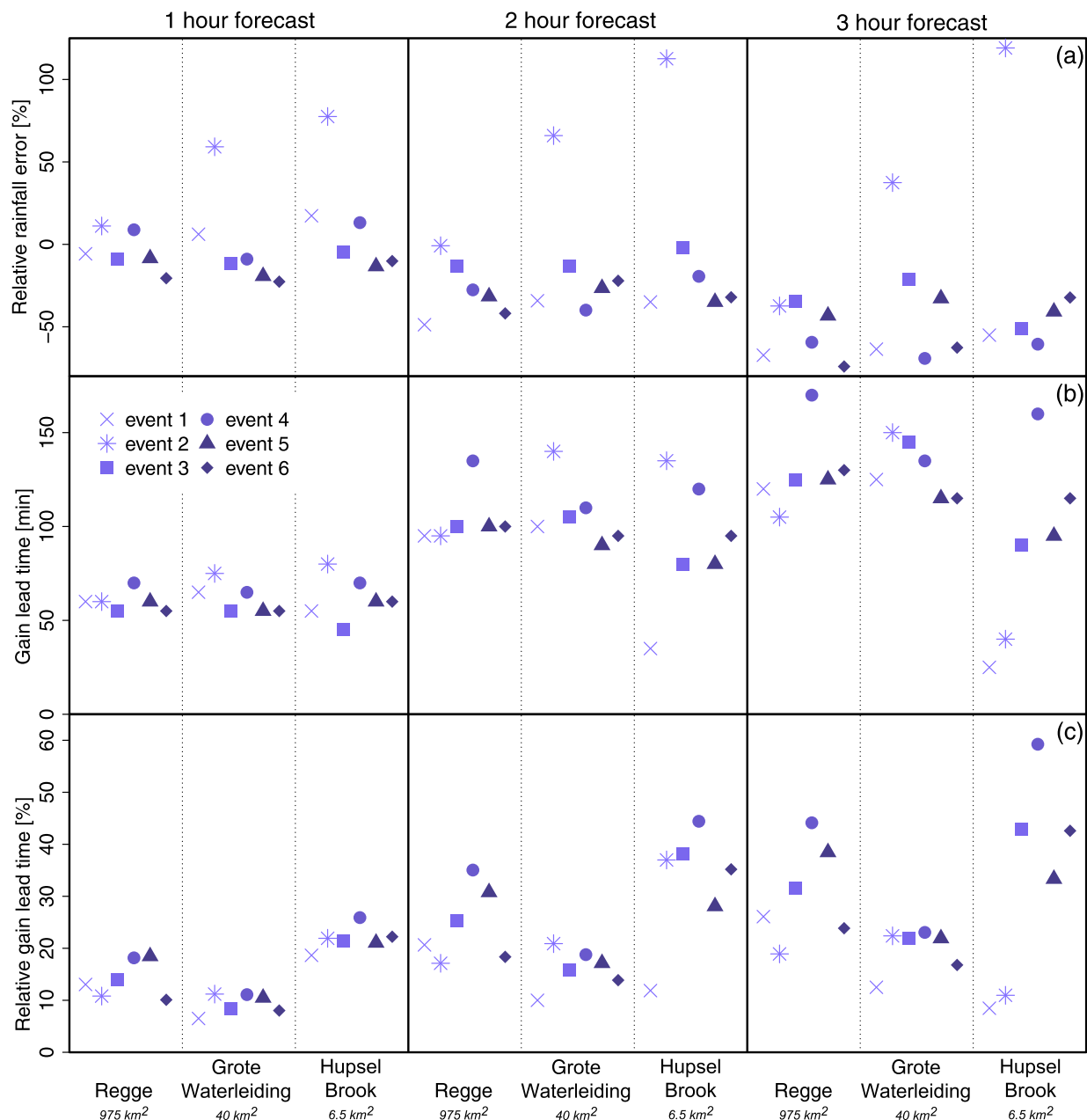
Similarly, the hydrological evaluation of the probabilistic radar rainfall nowcasts considers rainfall input series constructed by combining deterministic rainfall observations with probabilistic nowcasts (an ensemble of 10 members). These rainfall time series were used to simulate discharges with WALRUS in the same way as for the deterministic forecasts. The simulated discharges for the 10 ensemble members could not be used directly to calculate the gain in lead time for the ensemble forecasting, for the same reasons as for the rainfall validation. For every time step and lead time, the member for which the forecasted discharge was closest to the reference discharge was selected. This led to the *maximum* gain in lead time. For the *minimum* gain in lead time, for every time step and lead time the member for which the forecasted discharge was furthest from the reference discharge was selected. For these best and worse discharge forecasts, the lead time leading to an NS efficiency of 0.9 was calculated. By comparing the maximum and minimum gain in lead time the uncertainty associated with the gain in lead time for the deterministic nowcasting was assessed.

## 4. Results

### 4.1. Deterministic rainfall and discharge forecasts

The top row of Fig. 3 shows the relative rainfall error for the rainfall forecasted one, two and three hours ahead for all catchments and events. In general, rainfall appears to be underestimated, which becomes more severe with increasing lead time. This increasing underestimation can partly be explained by the spatial coverage of the radar. With increasing lead time, rainfall may have been outside the radar domain at the time at which the forecast was issued. Another cause is that growth and decay of rainfall, which is especially important for convective events, are not included in the Lagrangian persistence nowcasting approach. On the other hand, for some events and forecast durations, rainfall was overestimated. This happened most often and most severely for the Hupsel Brook catchment. For example, at a lead time of three hours, the rainfall amount for event 2 was overestimated with 120%. This can be explained by the size of the catchment and the type of event. The Hupsel Brook catchment is a small catchment, with only seven radar pixels falling inside the catchment. Therefore, this





**Fig. 3.** Results for one, two and three hours of deterministic nowcasts for all catchments and events: row (a) relative rainfall error of the forecasted rainfall, row (b) absolute gain in lead time and row (c) relative gain in lead time.

catchment is sensitive to the exact location of small rainfall systems. Especially for event 2, which is a more convective event with rain showers, the exact location of the rain was difficult to predict. A rainfall system was forecasted to pass over the Hupsel Brook catchment, but in reality, this rainfall system dissipated over land, so rainfall at the end of the event was overestimated.

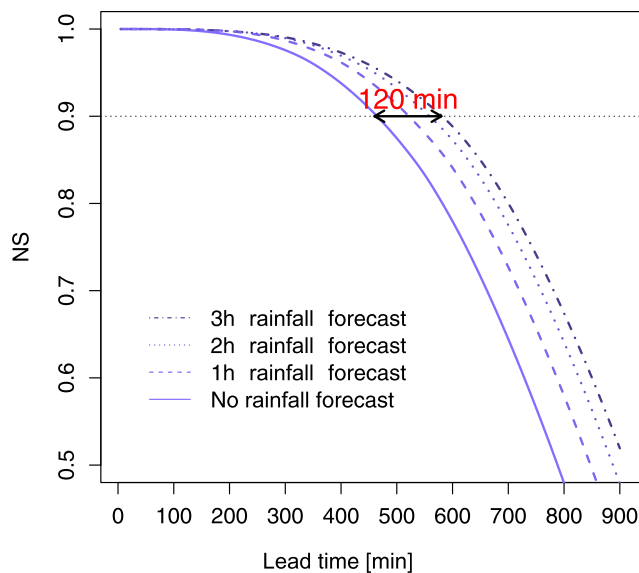
Fig. 4 shows the gain in lead time for event 1 for the Regge catchment. This shows the evolution of the NS efficiency of forecasted discharges with increasing lead time. The NS efficiency decreases with longer lead times, because the rainfall forecast worsens as lead times increase. The four lines represent the discharge forecasts corresponding to the different lead times of the forecasted rainfall time series with which WALRUS was run. The zero hour forecast shows the predictability of the discharge without forecasted rain. This serves as a baseline, to which the discharge forecasts with one, two and three hours of forecasted rainfall were compared. With three hours of forecasted rainfall, the discharge can be forecasted 120 min earlier, with an NS

efficiency of 0.9.

The middle row of Fig. 3 shows the gain in lead time for all events and catchments, for one, two and three hours of forecasted rainfall. Note that event 3 for the Grote Waterleiding catchment is missing, because the low rainfall amount did not cause a discharge peak given the catchment's slow response. For every catchment, there was a gain in lead time for the discharge forecast. This gain was highest with three hours of forecasted rainfall, but differed between catchments.

The difference in lead time gain between the events was large, especially for the Hupsel Brook catchment. For the Grote Waterleiding and the Regge catchments, the performance for the events varied less. The gain in lead time with a 3-h rainfall forecast differs significantly between the catchments. For example, event 2 scored the lowest for the Regge catchment and second lowest for the Hupsel Brook catchment, but highest for the Grote Waterleiding.

For event 2, the gain in lead time with one hour of forecasted rainfall for the Hupsel Brook catchment is 80 min, which is more than



**Fig. 4.** Nash-Sutcliffe (NS) efficiency of the discharge forecasts as a function of lead time for the Regge catchment and event 1. The black arrow shows the gain in lead time for which the discharge can still be forecasted with  $NS > 0.9$ , for the three hours of forecasted rainfall. The blue lines show the NS efficiency for discharge forecasts with zero, one, two and three hours of forecasted rainfall input. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the one hour lead time of the rainfall forecast put into it. This was also seen for event 4, for the one hour and the two hours of forecasted rainfall. This is caused by the overestimation of total rainfall for these events. The overestimation of rainfall causes the total volume of discharge to be closer to the reference discharge, even for longer lead times. The timing and height of the discharge peak may be different, but the fact that the total volume of discharge is closer to the reference leads to the higher gain in lead time.

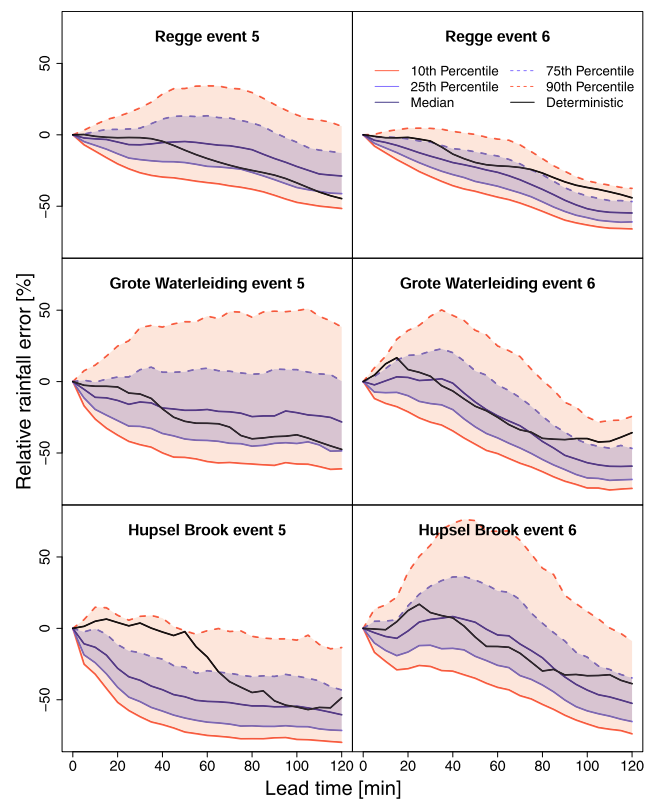
The relative gain was highest for the Hupsel Brook catchment, especially for the 1-h and 2-h forecasts (bottom row of Fig. 3), which can be explained by its fast response. For the 3-h forecast, there was a large difference between events, especially for the Hupsel Brook catchment, where the relative gain ranged from 10 to 60%. Similar to the absolute gain in lead time, a higher relative gain in lead time for one event in one catchment did not necessarily imply a higher relative gain in lead time for that event for one of the other catchments.

For the stratiform events, events 1, 3 and 6, the nowcasting did not lead to higher gains in lead time than for the more convective events. This was not as expected, since forecasting stratiform events should in general be easier than forecasting convective events. This is possibly due to the characteristics of the selected events, since there were no purely convective events and the events consisted of multiple rainfall peaks.

#### 4.2. Probabilistic rainfall and discharge forecasts

This section presents preliminary results concerning the coupling of SBMcast with WALRUS. The results are presented for the rainy periods of events 5 and 6. Fig. 5 shows the evolution of the relative rainfall error with increasing lead time. This is shown for the percentiles of rainfall for the ensemble nowcasting as well as for the deterministic nowcasting, for the three catchments.

There appears to be a clear difference between the catchments. The largest catchment, the Regge, shows the least variation in relative rainfall error. Due to the relatively large size of the Regge catchment



**Fig. 5.** Evolution of the relative rainfall error of the forecasted rainfall amounts with increasing lead time. The lines represent the percentiles, with the red and blue bands showing the spread. The black line shows the relative rainfall error for the deterministic rainfall nowcasts. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

uncertainties in the exact location of forecasted intense rainfall showers will have a smaller effect on catchment-average rainfall for the Regge catchment than for the other catchments. Therefore, the spread in forecasted catchment-average rainfall will be lower than for the other two smaller catchments. Moreover, variations in forecasted rainfall are more likely to compensate each other in a larger catchment. The spread for the Hupsel Brook catchment is the largest for event 6, but for event 5 the spread for the Grote Waterleiding is largest. The spread for the Hupsel Brook is not the largest for this event, because even the 90th percentile hardly shows an overestimation of forecasted rainfall. This is caused by the extreme amount of rain that actually fell during event 5: a record breaking rainfall amount of 160 mm in 24 h was observed, with an estimated return period of well over 1000 years (Brauer et al., 2011). A very intense convective rainfall system passed exactly over the Hupsel Brook catchment. Forecasting even more rainfall was therefore highly unlikely. This is supported by the underestimation of rainfall for the 10th percentile, which was the most severe for all events and catchments.

Overall, the spread for event 5 is larger than the spread for event 6. This is caused by the more convective nature of event 5. In convective situations, the forecasted rainfall at the catchment scale differs more between ensemble members than for stratiform situations. The majority of the rainfall in a convective event is determined by individual, intense showers. Especially these are perturbed for the ensemble members. The relative rainfall error for the deterministic nowcasts falls most often within the 25th to 75th percentile band of the relative rainfall error for the ensemble nowcasts. This suggests that ensemble rainfall nowcasting provides a good measure of the uncertainty associated with

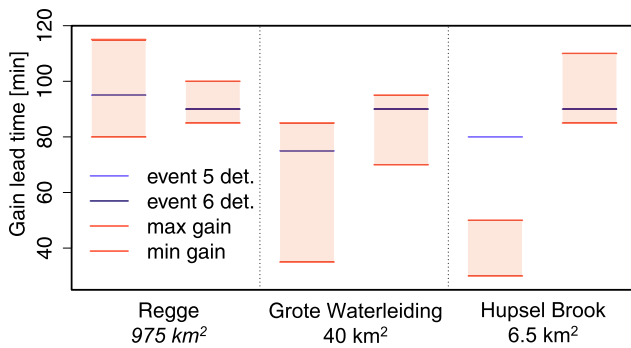


Fig. 6. Gain in lead time for events 5 and 6, for the three catchments. The solid blue lines show the gain in lead time for the deterministic nowcasts. The red shaded bands show the uncertainties associated with this gain in lead time derived from the ensemble nowcasts. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

deterministic rainfall nowcasts.

Fig. 6 shows the uncertainties in the gain in lead time for the deterministic nowcasts, based on the ensemble nowcasts. Overall, the uncertainties for event 5 are larger than for event 6. This is caused by the uncertainties in the forecasted rainfall, which was previously shown to be higher for event 5 than for event 6. The uncertainty associated with the gain in lead time is not equally spread around the gain in lead time found for the deterministic nowcasts. For the Grote Waterleiding catchment, the gain in lead time for the deterministic nowcasting falls in the top part of the uncertainty band, which implies that deterministic nowcasting in this case leads to an optimistic view of the gain in lead time. For the Regge catchment the gain in lead time lies just below the centre of the uncertainty band.

The largest uncertainty in gain in lead time can be seen for event 5 for the Grote Waterleiding catchment. This is caused by the large spread in the forecasted rainfall amounts. For event 6 for the Regge catchment the uncertainty in gain in lead time is lowest, as expected based on the limited uncertainty in the forecasted rainfall amounts. For event 6, the uncertainty associated with the gain in lead time is equal for the Grote Waterleiding catchment and the Hupsel Brook catchment. However, the spread in the rainfall forecasts is larger for the Hupsel Brook catchment than for the Grote Waterleiding catchment. This shows that it is difficult to compare the uncertainties between catchments, since there are catchment specific factors that could affect the extent of these uncertainties. These factors can for instance be the catchment response time, the initial conditions of the catchment and the relative contributions of quickflow and groundwater flow.

For event 5 for the Hupsel Brook catchment, the gain in lead time for the deterministic nowcasting falls completely outside the range of the uncertainty in the gain in lead time derived from the ensemble nowcasting. This is because this was an extreme event for the Hupsel Brook catchment, as mentioned before. As indicated by the relative rainfall error, for a lead time up to one hour the total rainfall is forecasted well with the deterministic nowcasting. Any perturbation to this introduced in the ensemble members can thus only lead to worse rainfall forecasts and thus worse discharge forecasts. The 10th percentile shows a relative rainfall error of around zero. However, this does not mean that the rainfall forecast is perfect. There is no information on the timing of the forecasted rainfall in the relative rainfall error. Any errors in the timing of the forecasted rainfall would affect the forecasted discharge as well. Because this was such an extreme event, the number of ensemble members is possibly too low to capture the actual uncertainty associated with forecasting this event. Increasing the ensemble size would increase the probability that individual members

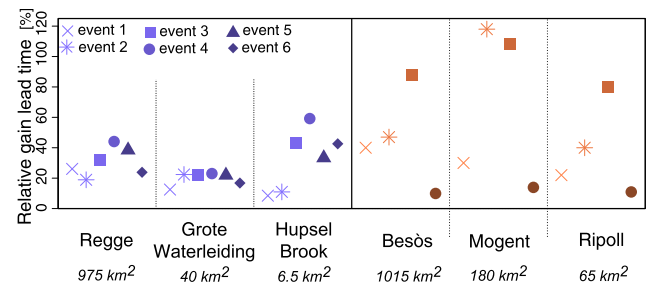


Fig. 7. Relative gain in lead time for 3-h rainfall forecasts in the Netherlands (this study, left) and 2-h rainfall forecasts in northeast Spain (Berenguer et al., 2005, right).

would forecast more rainfall for the Hupsel Brook catchment and thereby capture the uncertainty in the gain in lead time better.

## 5. Discussion

There are clear differences between the results for the gain in lead time for this study and the results found by Berenguer et al. (2005) in a very different climatic setting (northeast Spain). For instance, Berenguer et al. (2005) concluded that the third hour of rainfall forecasts did not improve the gain in lead time for the discharge forecasts. This is contrary to the results presented in this study, since second and the third rows of Fig. 3 show that for nearly all events and catchments the third hour does increase the gain in lead time.

The differences between the studies can be explained by differences between the considered catchments. The catchments studied by Berenguer et al. (2005) are rapidly responding, with lag times between one and two hours. The catchments used in this study respond much more slowly. For more quickly responding catchments it is more important that the rainfall is forecasted correctly, since the discharge signal is smoothed less than for more slowly responding catchments. For example, Fig. 4 shows a very smooth decrease of the NS efficiency with increasing lead time. Similar figures in Berenguer et al. (2005) are less smooth. This is also supported by Vivoni et al. (2006), who concluded that the discharge forecast quality deteriorates when the response of the catchment is faster than the lead time of the forecast. Berenguer et al. (2005) found gains in the lead time for the discharge forecast between 10 and 80 min. For this study the gain lies between 25 and 170 min, which is significantly longer. This is mainly caused by the slower responses of the catchments considered in this study. In addition, the events considered in this study were more stratiform, which is easier to forecast. Note that even the ~1000 km<sup>2</sup> Besòs basin from Berenguer et al. (2005) has a faster response time (~2 h) than the 6.5 km<sup>2</sup> Hupsel Brook catchment (~6 h).

The results of Berenguer et al. (2005) allowed a calculation of the relative gain in lead time as well. Fig. 7 shows the relative gain for the catchments and events considered in this study compared to the relative gain for the catchments and events considered by Berenguer et al. (2005). There appear to be some striking differences between the two studies. For Berenguer et al. (2005), there is more variation in the relative gain between catchments and between events. On average, not only is the relative gain higher for the cases studied by Berenguer et al. (2005), the differences between the cases are larger as well. This is caused by the quick response of the catchments by Berenguer et al. (2005).

Direct comparison with the study of Vivoni et al. (2006) is more difficult, since the methods used are very different. Nevertheless, a comparison can be made with the conclusions drawn in Vivoni et al. (2006). They found that the flood forecasting skill increased with catchment size, because of the reduced effect of rainfall nowcasting



errors for larger catchments. In this study, this could be seen for the rainfall forecasts, but not for the discharge forecasts, because flood forecasting skill also depends on the catchment response times. For the catchments considered by Vivoni et al. (2006), there was a clear correlation between catchment size and response time. For this study the Grote Waterleiding was the slowest responding catchment, although it was not the largest.

## 6. Conclusions

The main aim of this study was to investigate the added value of radar nowcasting for short-term rainfall and discharge forecasting for lowland catchments. This was achieved by using radar-based rainfall nowcasts as input for the hydrological model WALRUS for three catchments of different sizes and six rainfall events with different characteristics. Lagrangian persistence and SBMcast were used to produce deterministic and probabilistic rainfall forecasts, respectively, based on radar rainfall estimates in the Netherlands.

The results showed that the skill of deterministic rainfall nowcasting differed strongly between events. No clear differences between stratiform and convective events could be observed. This is probably because the distinction between stratiform and convective was not that clear for the events considered. All convective events were actually of a mixed stratiform-convective nature. In addition, with only six events, three events in each category (Table 1), the sample sizes were relatively small. The variability within each category was found to be of the same order as the differences between the categories. In general, the rainfall forecasting skill was found to decrease with increasing lead time, most often associated with underestimation of the forecasted rainfall. This is probably related to the fact that the considered nowcasting schemes do not explicitly take the possible growth of rain cells into account.

Application of the forecasted rainfall to discharge forecasting showed promising results. Radar rainfall nowcasting provided added value for the three catchments considered in this study: lead times increased between 25 and 170 min. However, there were significant differences between catchments and events. The largest increase in lead time was found for the largest catchment, and the smallest increase for the smallest catchment. The relative gain in lead time was in general the highest for the smallest, most quickly responding catchment, although this catchment also exhibited the largest differences between events.

The probabilistic nowcasting method considered in this study was applied to two events and found to address not only the uncertainty in the forecasted rainfall, but also in the forecasted discharge. The use of ensemble nowcasts provided a good assessment of the uncertainty associated with the forecasted rainfall and with the gain in lead time for the discharge forecast, with an uncertainty ranging from 15 to 50 min.

Comparison with other studies showed that the added value of radar rainfall nowcasting depends strongly on the type of rainfall event, the size of the catchment and the response time of the catchment. To better understand in what situations radar nowcasting performs best, more events and catchments need to be investigated. Also, to obtain a better appreciation of the associated uncertainties, large ensemble sizes should be considered.

It was shown that radar rainfall nowcasting can be beneficial for discharge forecasting in the Netherlands. This provides opportunities to use radar rainfall nowcasting in operational flood forecasting, enhancing the quality of the forecasted discharges on a short time-scale. Especially for urban catchments and catchments with control measures radar rainfall nowcasting could be beneficial for discharge forecasting. To enhance the applicability of this study, new radar products should be developed which are especially designed to overcome the bias present in current operational (real-time) radar products, with minimal losses concerning the predictability of rainfall. Further research should also include a larger number of events to allow drawing more robust conclusions and focus on using radar composites covering larger areas, to further enhance forecast lead times.

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